ARL-SR-0318 • MAR 2015

US Army Research Laboratory

Fundamentals of Adaptive Intelligent Tutoring Systems for Self-Regulated Learning

by Robert A Sottilare

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ARL-SR-0318 ● MAR 2015

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REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED (From - To)**
March 2015	Special Report	February 2014–December 2014

4. TITLE AND SUBTITLE Fundamentals of Adaptive Intelligent Tutoring Systems for Self-Regulated Learning	**5a. CONTRACT NUMBER** **5b. GRANT NUMBER** **5c. PROGRAM ELEMENT NUMBER**
6. AUTHOR(S) Robert A Sottilare	**5d. PROJECT NUMBER** **5e. TASK NUMBER** **5f. WORK UNIT NUMBER**
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) US Army Research Laboratory ATTN: RDRL-HRT-T Aberdeen Proving Ground, MD 21005-5425	**8. PERFORMING ORGANIZATION REPORT NUMBER** ARL-SR-0318
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)** **11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The tutorial described in this report was conducted at the Interservice/Industry Training Simulation and Education Conference (IITSEC) in Orlando, FL, in December 2014. The purpose of this tutorial is 5-fold: 1) understand the differences between adaptive and adaptable systems; 2) understand the key components of Intelligent Tutoring Systems (ITSs); 3) understand the potential of ITSs as one-to-one tutors and where ITS technologies are most applicable in the training and educational domain; 4) understand the concept of self-regulated learning (SRL); and 5) understand how ITS design can support SRL.

15. SUBJECT TERMS

adaptive tutoring, intelligent tutoring systems, self-regulated learning, authoring adaptive systems, adaptive instruction, educational technology

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
					Robert A Sottilare
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER (Include area code)**
Unclassified	Unclassified	Unclassified	UU	34	407-208-3007

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

Contents

List of Figures

List of Tables

1. Tutorial Objectives

The purpose of this tutorial is 5-fold:

- Understand the differences between adaptive and adaptable systems
- Understand the key components of Intelligent Tutoring Systems (ITSs)
- Understand the potential of ITSs as one-to-one tutors and where ITS technologies are most applicable in the training and educational domain
- Understand the concept of self-regulated learning (SRL)
- Understand how ITS design can support SRL

2. Questions and Answers about Adaptive Tutoring

To set the stage for subsequent elements of this presentation and to level-set knowledge within the audience, we present 4 key questions about adaptive tutoring and their corresponding answers.

2.1 Question 1: What Is an Intelligent Tutoring System?

An ITS is a computer system that aims to provide immediate and customized instruction or feedback to learners, usually without intervention from a human teacher (Psotka and Mutter 1988). Koedinger and Tanner (2013) also describe an intelligent tutoring system as computer software designed to simulate a human tutor's behavior and guidance. ITSs may also be defined as computer-based instructional systems with models of instructional content that specify what to teach and teaching strategies that specify how to teach (Murray 1999; Wenger 1987; Ohlsson 1987).

2.2 Question 2: How Are Intelligent Tutoring Systems Different from Computer-Based Training Systems?

Computer-Based Training (CBT) systems are software-based and use computers to deliver instruction. CBT is also known as Technology-Based Training, Computer-Based Instruction, Computer-Assisted Instruction, or Computer-Based Learning.

ITSs are a subset of CBT. CBTs deliver instruction consistently to all learners, whereas ITSs are "intelligent". This implies their ability to adapt or tailor instruction in real-time based on triggers, which are usually defined as policies sometimes called “production rules”. Triggers are usually changes to the learner’s state(s) or the training environment. Policies are used by the tutor to recognize changes and learning opportunities (e.g., teachable moments) and trigger actions by the tutor.

2.3 Question 3: What Is an Adaptive System and How Is It Different from an Adaptable System?

Adaptable systems may be changed by the user. Flexible control of information or system performance automation resides in the hands of the user (Oppermann 1994). A smartphone user interface is adaptable and may be configured to support the specific educational or entertainment needs of the user.

Adaptive systems change behaviors based on observations of changing conditions in the user and/or the environment. In adaptive training systems, the agents observe and interpret each learner’s data (behaviors and physiology) to determine learner states (e.g., engagement, emotions, performance) and identify individually tailored learning needs. They respond to the learner’s states and needs by adjusting the challenge level of scenarios and amount/type of tutor support in near real time to maximize training effectiveness (e.g., performance, learning, retention, and transfer).

System change is usually managed by software-based agents who use artificial intelligence techniques to guide their decisions and actions. Software-based agents vary in their reactivity, proactivity, and cooperation. Examples of artificial intelligence techniques for managing adaptive training policies include the following:

- Production Rules
- Decision Trees
- Neural Networks
- Bayesian Networks
- Reinforcement Learning Algorithms
- Markov Decision Processes

Reactive agents respond to changes in the training environment or the learner and are active in assessing conditions related to policies that they are assigned to enforce. Proactive agents take initiative to achieve long-term goals and recognize opportunities (e.g., teachable moments). Proactive agents also learn and adapt through experience. Finally, cooperative agents share information and act together to achieve long-term goals.

Both adaptable and adaptive systems have the flexibility to change in the face of changing conditions, but adaptive systems have advantages in being able to offload control tasks to agents (Miller et al. 2005) resulting in

- greater speed of performance,
- reduced human workload, more consistency, and
- a greater range of flexibility in behaviors.

An example of an adaptive tutoring method based on a learning theory is Component Display Theory (CDT; Merrill et al. 1992). As shown below, CDT asserts that the optimal method to effective learning is as follows:

- Gain attention and motivate.
- Adapt to the learner's prior knowledge.
- Adapt to the type of knowledge being presented.
- Adapt to learner attributes.
- Adapt to the learner's ability (intelligence, emotional intelligence, adaptability).

CDT specifies 4 quadrants for progressive stages of learning: rules, examples, recall, and practice (Fig. 1). Rules provide the basic principles needed to learn in a particular domain. Examples provide successful models of how to do a specific task in the domain. Recall provides assessments of the learner's ability to recollect facts and methods from the rules and examples quadrants. Finally, the practice quadrant provides opportunities for the learner to apply knowledge and skills learned and reinforced in previous quadrants. Each of these quadrants requires that the tutor recognize the learner's progress and states that moderate learning (e.g., emotion, workload, engagement). This recognition of changes in the learner is managed by adaptive agents.

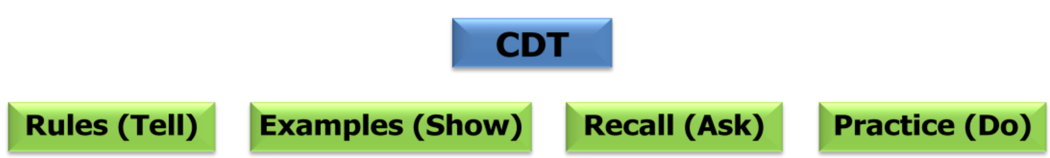

Fig. 1 Merrill's Component Display Theory

Another adaptive tutoring method is based on the adaptive tutoring Learning Effect Model (LEM; Sottilare 2012; Fletcher and Sottilare 2013; Sottilare 2013; Sottilare et al. 2013) as shown in Fig. 2. LEM, a learner-centric model, is largely domain independent. As such, LEM can be applied in a variety of domains with a variety of learners. LEM is the basis for the Generalized Intelligent Framework for Tutoring (GIFT; Sottilare et al. 2012), a modular architecture for automatically managing instruction.

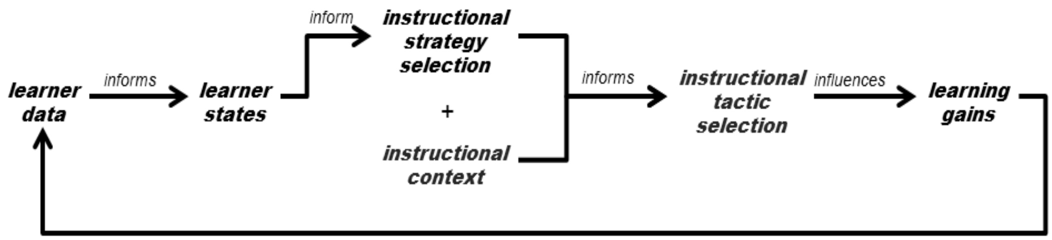

Fig. 2 Sottilare's Learning Effect Model

2.4 Question 4: What Is Self-Regulated Learning?

To discuss SRL, we must first define self-regulation, which is controlling, adjusting, or conforming to standards without intervention from external entities. SRL is learning managed by the learner and guided by the processes of metacognition and motivation. Metacognition is thinking about how one thinks and learns (e.g., reflection about the learning process). Motivation is the importance or enthusiasm to take actions needed to learn and is closely tied to individual goals and values. ITSs can influence the success of SRL by influencing/reinforcing metacognition and motivation through scaffolding/ support.

3. Characteristics of Intelligent Tutoring Systems

In this section we will explore how ITSs function, what they look like, their scope of use, and their ideal characteristics. ITSs are adaptive systems that may be designed to recognize and adapt to a variety of changing conditions in both the learner and the environment (see Fig. 3).

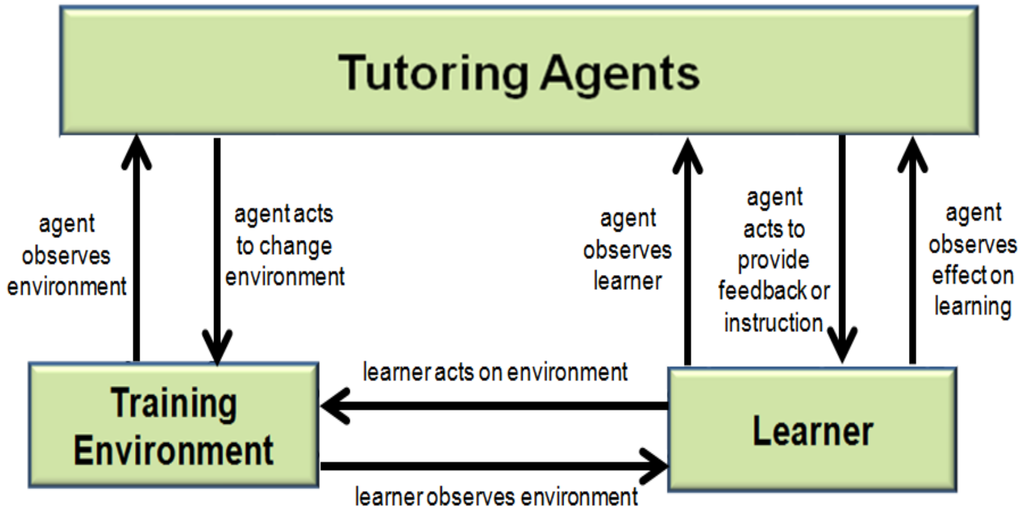

Fig. 3 Adaptive training interaction between learner, training environment, and tutor

To support interaction between the learner and the logic of the ITS, ITSs have a variety of interface controls and information delivery windows that make up a tutor-user interface, or TUI (see Fig. 4). Typical functions for TUIs for ITSs include the following:

- **Content presentation window.** This window provides multimedia content in support of learning objectives.
- **Tutor natural language feedback window.** This window provides a human representation to converse with the learner and provides questions, hints, prompts, direction, support, and other feedback to the learner verbally. Natural language responses from the learner are converted to text and analyzed by the ITS. Then, an appropriate response is selected, and natural language is generated and delivered by the virtual human.
- **Tutor text feedback window.** This window offers the option of providing text feedback in the absence of a natural language interface or in addition to a natural language interface.
- **Learner response window.** This window provides the learner with the option of typing responses to questions or other queries by the ITS.
- **Conversation log.** This window tracks conversation between the learner and the ITS so the learner can refer to it at a later date; this information might also be used by the tutor to support non-real-time feedback (e.g., after-action review).

Fig. 4 Composite ITS interface

So now that we know what ITSs look like, what their interface functions are, and that they interact with both the learner and the training environment, let us discuss how they work in real time. Nearly every tutoring system has 4 fundamental elements: a learner model, a pedagogical (instructional) model, a domain model, and a communication model. Figure 5 shows a functional diagram of the information flow between various modules in a tutoring system. This flow diagram is modeled after the information flow in GIFT and, specifically, the LEM discussed previously.

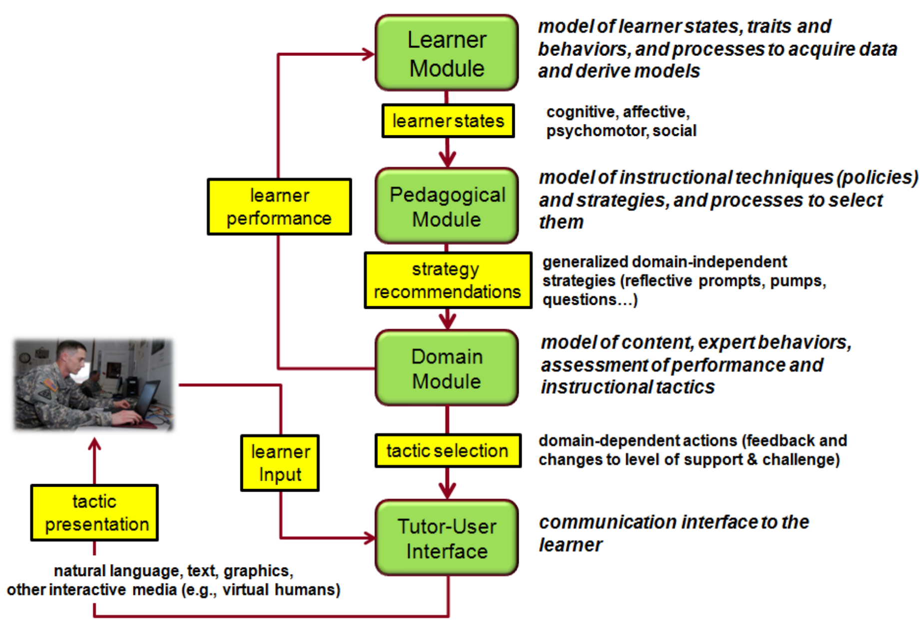

Fig. 5 Data flow in ITSs

The green boxes above show these fundamental elements as *modules* vs. models because they manage processes in addition to modeling the learner, the instruction, the domain, and the communication to/from the learner. The TUI has been discussed in detail, so now the learner, pedagogical, and domain modules will be reviewed:

- **Learner module.** In addition to receiving learner performance states (at, below, or above expectation) from the domain module, the learner module also uses real-time behavioral and physiological data along with historical (e.g., progress toward objectives) and demographic data to classify learner cognitive, affective, physical, and shared states, which are provided to the pedagogical module.

- **Pedagogical module.** The pedagogical module models the instructional techniques (policies) and strategies (plans), and uses these to develop recommendations for execution by the domain module.

- **Domain module.** The domain module models the content, expert behaviors, measures of learning, and performance, and uses these to assess learner progress against expectations; it combines this information with strategy recommendations from the pedagogical module to select a tactic or action that provides media or interaction data to the TUI for display or natural language generation.

There are various types of tutors, but they can be generally grouped into 2 primary categories based on their underlying instructional models:

- Example-tracing tutors (also called ray-tracing or model-tracing tutors) are fixed in how they instruct, but they can be created without programming, and they require problem-specific authoring.

- Cognitive tutors are more flexible and adaptive but required longer development time because of the requirement to build a cognitive model of the learner; they support tutoring across a range of similar problems.

Some tutors may be classified as “shell” tutors. In other words, they are templates or frameworks to support the development of tutors in a variety of domains. One shell tutor is GIFT (Fig. 6)—a free, open-source tutoring architecture to

- capture best tutoring practices; support rapid authoring, reuse, and interoperability of ITSs;

- lower costs and entry skills needed to author ITSs; and

- enhance the adaptiveness of ITSs to support SRL.

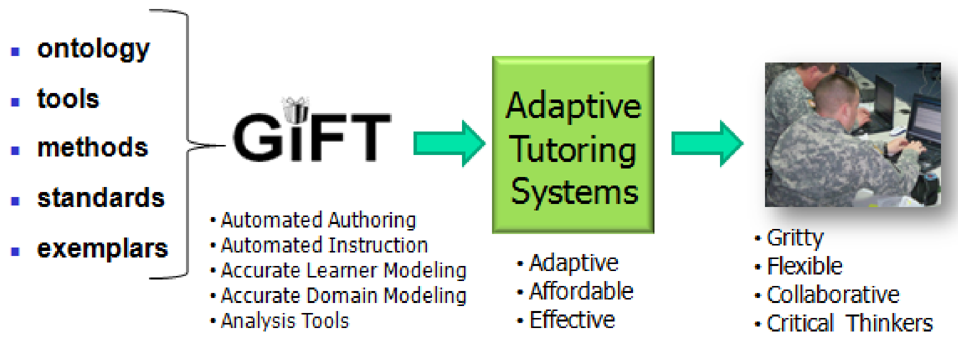

Fig. 6 The Generalized Intelligent Framework for Tutoring (GIFT)

Another class of tutors is "dialogue-based tutors", which provide for Socratic interaction between the learner and tutor. An example of a dialogue-based tutor is AutoTutor, shown in Fig. 7.

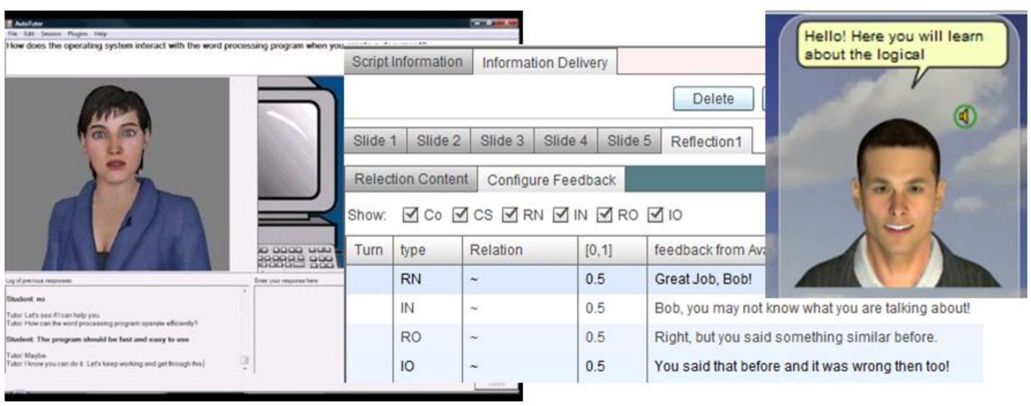

Fig. 7 Examples of dialogue-based tutors: AutoTutor and AutoTutor Lite

Now that we've identified various types of ITSs, let us list the salient characteristics we would like to see in adaptive tutoring systems. Sottilare and Gilbert (2011) identified several ideal characteristics in their "platinum level tutor" for Army training:

- Self-regulated: Support learning of individuals and teams.
- Adaptive: Use artificial intelligence to tailor instruction to the learning needs of individuals and teams.
- Effective and credible: As good or better than an expert human tutor.
- Relevant: Support military training in both ill-defined and well-defined environments.

- Accurate and valid: Use optimal instructional methods based on empirical results.
- Usable: Tailored to different users (learners, authors, researchers, etc.).
- Accessible: Service-oriented and available anywhere 24/7/365.
- Affordable: Easy to author and promotes standards and reuse.
- Persistent: Models the learning needs of Warfighters across their careers.

Now that we have reviewed what ITSs are, how they work, and what we want them to be, let us identify the domains they are good at training. In Fig. 8, we have identified what we believe to be an optimal domain for using ITSs.

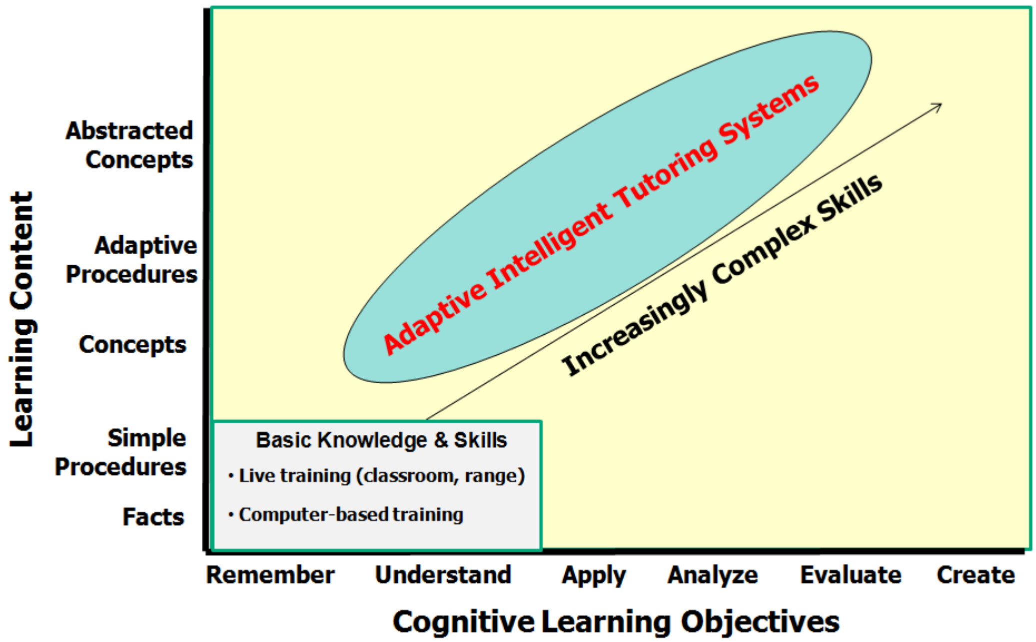

Fig. 8 What are adaptive ITSs good at training?

Specifically, we have plotted cognitive learning objectives (x axis) identified by Bloom et al. (1956) in their cognitive taxonomy against the complexity of the learning content (y axis) to be presented to the user. Based on the time and skills needed to author an ITS, we envision the best application of this technology is in complex domains with complex learning content and high learner throughput. However, we also recognize that technologies are being developed to lower the bar for the skills and time it takes to author ITSs. In the future, ITSs must be suitable for teaching across all levels of domain complexity—even in courses where there is low throughput.

In light of this pending revolution, we recommend using ITSs for teaching tasks across the following domains:

- Cognitive (e.g., complex decision making, strategic thinking, problem solving)
- Affective (e.g., interpersonal skills, ethical conduct)
- Psychomotor (e.g., operating sophisticated weapons/platforms)
- Social (e.g., collaborative and team tasks)

We also recommend using ITSs to prepare for live training/practice; to enhance learning within virtual training environments; and to support intelligent decision-aiding/mentoring on the job. The motivation for making the investment to use and improve ITSs is discussed in the next section.

4. Motivation for Using and Improving Intelligent Tutoring Systems

Today, ITSs have been primarily limited to well-defined domains, such as physics, mathematics, chemistry, and software development. ITSs are expensive and require specialized skills to author them. They are insufficiently adaptive to support highly effective, tailored training experiences across the broad spectrum of tasks conducted by our military today. Given the limited set of applications and functional limitations, what is our motivation for using and improving ITSs?

First, there is a need. A smaller force requires each Warfighter to have expertise in a greater range of skills for complex missions. We need to achieve expertise faster with fewer resources. To do this we will need to tailor training and take advantage of what learners already know. Second, there is an opportunity to accelerate the development of expertise by developing ITSs as effective as expert human tutors, with cost-effective features. Finally, ITSs have been shown to be highly effective (Fig. 9), so the promise of gold is there if we dig a little.

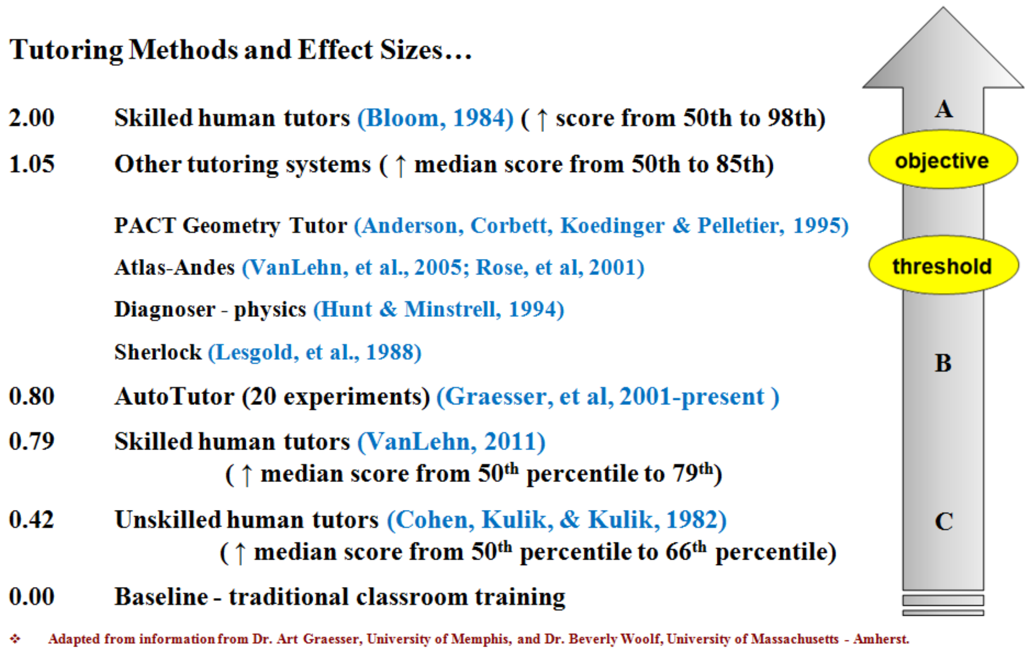

Fig. 9 Motivation for adaptive tutoring systems: they work

5. ITS Design in Support of Self-Regulated Learning

Since one of our goals is to support SRL, how can we design ITSs to support SRL? Four areas of opportunity are influencing the design of learner models, instructional models, domain models, and user interfaces. Given the time for this tutorial, we will focus on the first 3 in this report and leave the discussion of user interfaces for another time.

By understanding the relationship between learner data, learner states, instructional strategies, context and tactics, and learning gains (e.g., performance, learning, retention, and transfer) as noted in the LEM (Fig. 10), we can influence the process of SRL.

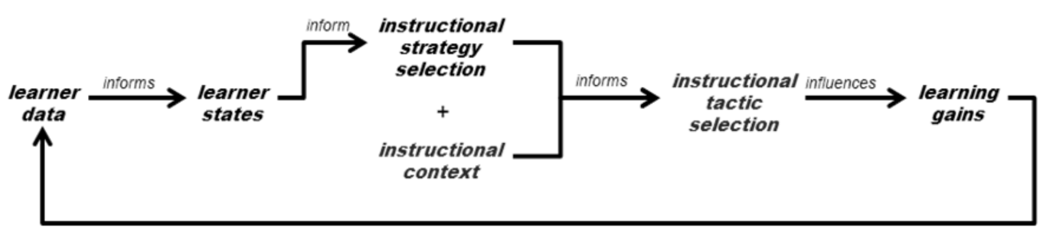

Fig. 10 Sottilare's Learning Effect Model

5.1 Learner Modeling in Support of Self-Regulated Learning

In this section we will discuss the relationship between learner data acquisition and learner state classification. Understanding the state of the learner is critical to successful tutoring. Successful human tutors are experts at recognizing telltale signs in their students that infer whether their students are learning or not. To support SRL, computer-based ITSs must also be able to interpret learner data to classify learner states (e.g., confusion, frustration, boredom), which moderate learning gains.

Sensors are one method of acquiring data about the learner. One approach is to investigate low-cost sensor technologies to inform classification of key influencers of learning. The results of a survey of low-cost behavioral and physiological sensors (Carroll et al. 2011) are shown in the Table below, along with the states that they are best at classifying and their cost.

Table Low-cost behavioral and physiological sensors

States	Sensor	Cost ($)
Anger/Frustration, Boredom	Motion detector	~100
Anger/Frustration, Fear/Anxiety, Boredom	Heart rate monitor	~100
Anger/Frustration, Boredom	Chair pressure sensors	~200
Engagement	Chair pressure sensors	~200
Attention, Engagement, Workload	EEG	~200
Attention, Workload	Eye tracker	~500

Other methods of acquiring data include surveys and assessments, and reading data from accessible databases (e.g., personnel records, learning management systems). Learner data may be labeled (supervised), unlabeled (unsupervised), or semi-supervised. Once you have learner data, this can be used to interpret various learner states using a variety of machine learning techniques.

Since training is a real-time process, we want to provide feedback to the learner in close time proximity to the event of interest. We want learner state classification processes that are also real time to maintain the close coupling of interaction between the learner and the tutor. Along with motivation, some of the key learner states are moderators or influencers of learning are cognitive (e.g., attention, engagement, cognitive load) and others are affective (e.g., confusion, boredom, frustration, anxiety, anger). It is essential for the ITS to be able to recognize and react appropriately to these states to either optimize positive influence or mitigate negative influence.

In investigating significant influencers of learning, we found the following in the literature or through our own investigations:

- Cognitive modeling: cognitive load, engagement (Lepper and Woolverton 2002); attention, distraction, drowsiness, engagement, flow, and workload (Carroll et al. 2011; Kokini et al. 2012)
- Motivational modeling: personality, values, goals, interests (Lepper and Woolverton 2002)
- Affective modeling: confusion, boredom, frustration, engagement/flow, curiosity, anxiety, delight, and surprise (Graesser and D'Mello 2012); mood modeling—pleasure, arousal, and dominance (Mehrabian 1996; Sottilare and Proctor 2012; Brawner 2013)

A study by Brawner (2013) examined methods to classify cognitive and affective states. One goal is to be able to build classifiers that can be applied across populations. Brawner found that generalized classifiers were proving to be impractical because of individual differences. Offline individual classification models turned out not to be reusable on the same individuals due to changes in physiology from one day to the next. Real-time classifiers of affect were of good quality (~80% accurate), but real-time classifiers of cognition were not as good (<60% accurate).

Brawner's study used a variety of classification methods. If you are interested in other machine learning techniques, check out WEKA, an open-source software tool for machine learning: http://www.cs.waikato.ac.nz/ml/weka/.

5.2 Instructional Management in Support of Self-Regulated Learning

In this section we will discuss the relationship between learner state and the development of instructional techniques (policies) and instructional strategies (plans). We previously discussed CDT (Merrill et al. 1992) as a method of managing instruction based on learning theory. The construct of CDT forms the basis for policies implemented in GIFT. Policies are rules or constraints that the ITS agents monitor to manage the flow, pace, and challenge level of the instruction based on the states and progress of the learner. Strategies are the recommended plans or course of action that the ITS develops based on the learners states. Tactics, which are implemented by the domain module, are actions formulated by the ITS based on the strategy recommendations and the specific domain context (who, what, where, when, and how).

CDT is just one approach to instructional management in support of SRL. Just about any learning theory could be instantiated in a tutoring framework to support SRL, but policies must be deconflicted to prevent paradoxes and ambiguities, which might result in negative training. This is why intelligent agents are critical to monitoring policies and decisions by the tutor.

Another approach to instructional management in support of SRL is modeling the behaviors, processes, and successes of expert human tutors as follows:

- INSPIRE model (Lepper et al. 1997). (INSPIRE = intelligent, nurturant, Socratic, progressive, indirect, reflective, and encouraging.)
- Facts about human tutoring (Person and Graesser 2003)
- Importance of questioning (Dillon 1988)
- Relation between deep reasoning questions and exam scores (Graesser and Person 1994)
- Politeness strategies (Person et al. 1995)

Another approach is to mimic ITS processes, which have been applied and have been shown successful over time. Such a process developed by Person et al. (1995, p. 167) has been applied extensively in dialogue-based tutoring, as shown in Fig. 11.

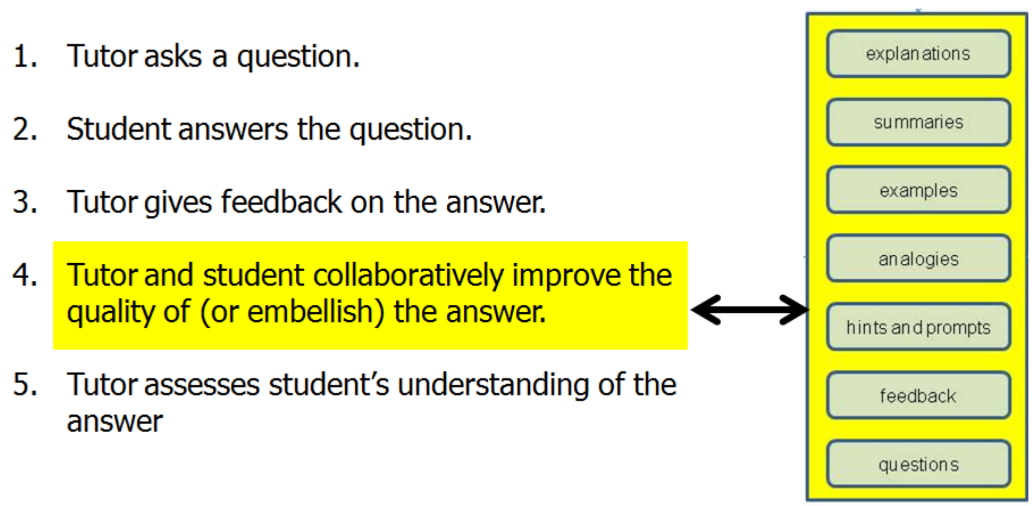

Fig. 11 Application of Person's (1995) 5-step tutoring process

Another approach is to investigate the learner's perception of the tutor to identify specific characteristics that influence learning. Anything that enhances the relationship between the learner and the tutor will result in fewer interventions by the tutor (resulting in more efficient learning processes) and higher levels of engagement (resulting in more opportunity to learn). Studies identified in the literature related to learner perception of the tutor are as follows:

- Credibility and supportiveness of the tutor (Holden 2012)
- Learner expectations of the tutor (Holden and Goldberg 2011)
- Social pedagogical agents (Kim et al. 2008)
- Characteristics of learning companions (Kim 2007; Kim et al. 2007)

A future approach to instructional management for SRL during tutoring is to evaluate the relationship between successful instructional strategies and the domains in which they are applied. One way to segregate this domain analysis is along the lines of Bloom's taxonomy (1956; cognitive, affective, psychomotor, and social) and examine which strategies are most successful in each domain. Later these might be applied as policies for tutoring in that domain. In order to instruct effectively in a domain, we must understand how to measure success of the learner in order to develop appropriate strategies. Bloom's taxonomy identifies hierarchies that might be used in the future to measure learner success in a broad domain. For example, affective learning is related to values, and one of the high-level behaviors of learners that indicate emotional growth is organizing values into priorities by comparing, relating, and synthesizing values to support decision making. The ability of the tutor to recognize this state will allow more effective decision making and enhanced learning.

5.3 Domain Modeling in Support of Self-Regulated Learning

In this section we will discuss the process of ITS decision making leading to tactic selection and delivery. Tactics are actions by the tutor that vary by domain. Tactics employed during cognitive tasks differ from those employed during psychomotor tasks. In order to grow ITSs beyond desktop training domains to more complex and dynamic military tasks, we need to examine how tactics will change and how the mode of delivery will also be affected. As shown in Fig. 12, we have identified 3 dichotomies for expanding the application of ITSs into military domains.

The simple-complex dichotomy is probably the easiest to tackle in the near term. Complex tasks can be segregated into a number of simpler tasks for presentation to the learner. The well-defined–ill-defined dichotomy is more difficult to implement. Given the nature of ill-defined tasks, intermediate measures of success are more difficult to define, so there is heavy emphasis on outcomes (e.g., performance), making it difficult to author instruction. An example of an ill-defined domain is leadership in a military context and hitting a baseball or golfing in a civilian context.

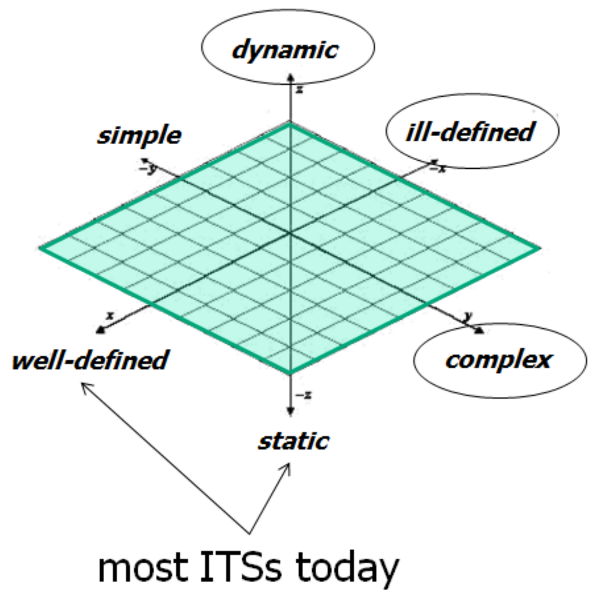

Fig. 12 Dimensions of domain modeling for military training

Finally, in the third dichotomy, static-dynamic, the concept is to more closely match the mode of interaction with the nature of the task. In other words, it is reasonable and effective to train a cognitive task (e.g., decision making) in a desktop training environment (e.g., game-based tutor), but it may not be as effective to train a psychomotor task (e.g., marksmanship or repelling) in a desktop or static mode because there is not an opportunity for learners to train as they would in the operational environment. For this reason, we developed a hierarchy of interaction for various tasks, as shown in Figs. 13–16.

Static environments (desktop mode) support purely cognitive and affective tasks where a low degree of interaction with the environment and other learners is critical to learning, retention, and transfer to the operational environment. Decision-making and problem-solving tasks are taught easily in a static mode, as shown in Fig. 13.

Interaction Mode	Environment	Learner Position	Learner Motion	Sensors	Sensory Interaction
static	indoor	seated	head motion, posture changes, gestures	desktop sensors (e.g., eye tracker, head pose estimation)	visual, aural, olfactory

Fig. 13 Static or desktop interaction with adaptive tutors

Limited kinetic environments support hybrid (cognitive, affective, psychomotor) tasks where a larger degree of interaction with the environment and other learners is critical to learning, retention, and transfer to the operational environment. Decision-making and problem-solving tasks may be taught easily in a limited kinetic mode along with tasks requiring physical orientation (e.g., land navigation), as shown in Fig. 14.

limited kinetic	indoor in confined instrumented spaces	standing, crouching, kneeling, laying	same as static mode plus limited locomotion	same as static mode plus motion capture	visual, aural, olfactory, haptic

Fig. 14 Limited kinetic interaction with adaptive tutors

Enhanced kinetic environments support tasks where freedom of movement and a high degree of interaction with other learners are critical to learning, retention, and transfer to the operational environment. Building clearing and other team-based tasks may be taught easily in an enhanced kinetic mode, as shown in Fig. 15.

enhanced kinetic	indoor/outdoor in confined instrumented spaces	standing, crouching, kneeling, laying	same as static mode plus full locomotion	same as static mode plus motion capture	visual, aural, olfactory, haptic

Fig. 15 Enhanced kinetic interaction with adaptive tutors

In the wild mode is transferring tutoring to the operational environments and could also be called embedded training for Soldiers. In the wild mode is critical to support tasks where a very high degree freedom of movement and a high degree of interaction with other learners are critical to learning, retention, and transfer to the operational environment. Psychomotor and social tasks may be best taught in the wild, as shown in Fig. 16.

in the wild	outdoor in unrestricted, uninstrumented spaces	standing, crouching, kneeling, laying	unrestricted natural movement	portable sensor suites including motion capture	visual, aural, olfactory, haptic

Fig. 16 Adaptive tutoring in the wild

The challenge with each of these modes is the increasing difficulty of unobtrusively acquiring their data, classifying their states, and providing relevant, real-time feedback to one or more members of a team.

5.4 Authoring in Support of Self-Regulated Learning

In this section we will discuss the process of ITS authoring or development. To support SRL, authoring processes must be able to support extensively adaptive training scenarios that tailor learning to a high degree. To support higher levels of adaptiveness (read this as larger numbers of options), authoring becomes more complex and tedious unless the authoring process can be streamlined. Two principles can be applied to the authoring process to reduce the author's workload but still allow flexibility for the author to control the instructional process in detail if needed.

Principle #1: Avoid Authoring by Promoting ITS Standardization, Interoperability and Reuse

Promote modularity to a large degree within the authoring process. Standards for processes, interaction, and exchange of data between modules (read this as a framework) will reduce the need for authoring. Standardization will also allow for reuse on a large scale. Templates and graphical interfaces will reduce workload and allow authors to organize knowledge and content.

Principle #2: Avoid Authoring through Automation

Wherever you are unable to avoid authoring new content, employ automation. Evaluate processes to determine the most tedious as candidates for automation. Processes that must be repeated frequently are candidates for automation. Within GIFT we automated a large portion of the expert modeling process, which is used to model the ideal learner for a particular domain. Artificial intelligence techniques in the way of job aids can be used to guide new authors through the authoring process.

This section and the tutorial ended with a demonstration of the GIFT authoring tools.

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